EVALUATION OF PERFORMANCE AND POWER CONSUMPTION WHEN DIFFERENT CONTROLLERS ARE USED ON ADAPTIVE CRUISE CONTROL OF AN ELECTRIC VEHICLE

by

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EVALUATION OF PERFORMANCE AND POWER CONSUMPTION WHEN DIFFERENT CONTROLLERS ARE USED ON ADAPTIVE CRUISE CONTROL OF AN ELECTRIC VEHICLE

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ABSTRACT

EVALUATION OF PERFORMANCE AND POWER CONSUMPTION WHEN DIFFERENT CONTROLLERS ARE USED ON ADAPTIVE CRUISE CONTROL OF AN ELECTRIC VEHICLE

Research on electric vehicles became a very hot topic in the last few years because they have advantageous in terms of efficiency, carbon emission and performance compared to combustion engines. However, high battery cost, long charging time and limited traveling range of electric vehicles are the challenges that researchers are still currently working on. Innovative battery and its management systems have been developed to increase travelling range of electric vehicles. Furthermore, lowering the battery power consumption of the comfort and safety systems in the vehicle is another research topic to increase battery range. Adaptive Cruise Control (ACC), which is one of the comfort and safety systems, has also been used to increase the travelling range of electric vehicles. In this thesis, we design ACC with three well-known Proportional-Integral-Derivative (PID), Fuzzy and Model Predictive Controller (MPC) controllers, and evaluate their acceleration/deceleration performance, and power consumption. Initially, the dynamic model of an electric vehicle (LCV), which includes electric vehicle longitude dynamic, and battery consumption equations, is developed. Later, ACC mathematical equations with Proportional-Integral-Derivative (PID), Fuzzy and Model Predictive Controller (MPC) are derived, and integrated inside the dynamic model of the electrical vehicle. Simulation experiments are performed to evaluate the performance and power consumption when these three controllers are used on ACC of the electrical vehicle.

ÖZET

ADAPTİF HIZ SABİTLEME SİSTEMİNDE FARKLI KONTROLÖRLER KULLANILMASI İLE ELEKTRİKLİ ARACIN PERFORMANS VE GÜÇ TÜKETİMİNİN DEĞERLENDİRİLMESİ

Elektrikli araçların içten yanmalı motorlara sahip araçlara kıyasla verimlilik, karbon emisyonu ve performans avantajları elektrikli araçlar üzerine yapılan araştırmaların gündemde olmasını sağlamaktadır. Bununla birlikte, elektrikli araçların batarya maliyetinin yüksekliği, uzun şarj süresi ve düşük menzil sorunları araştırmacıların halen üzerinde çalıştıkları konulardır. Yenilikçi batarya teknolojileri üzerine çalışmaların olması ile birlikte, araç içinde konfor ve güvenlik amaçlı kullanılan sistemlerin çalışma prensiplerinde de batarya güç tüketim değerlerini düşürerek araç menzilini arttıracak araştırmalar yapılmaktadır. Konfor ve güvenlik sistemlerinden biri olan Adaptif Hız Sabitleme (AHS) teknolojisinin batarya menzilini arttırmak için kullanılması bu çalışma alanlarından biri olarak gösterilmektedir. Bu tezde bilinen üç denetçi Oransal-Integral-Türevsel, Bulanık ve Model Öngörümlü denetçileri AHS ile kullanılarak farklı tip denetçilerin elektrikli aracın hızlanma/yavaşlama performansına, ve batarya tüketimine etkisi değerlendirilmiştir. Öncelikle elektrikli aracın yataydaki dinamik ve batarya tüketim davranışları modellenmiştir. Daha sonra Oransal-Integral-Türevsel, Bulanık ve Model Öngörümlü denetçiler ile birlikte oluşturulan AHS matematiksel denklemleri elektrikli araç dinamik modeline entegre edilmiştir. Simülasyon ortamında her bir denetçinin elektrikli aracın performans, ve batarya tüketim değerleri üzerine etkisi değerlendirilmiştir.

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LIST OF SYMBOLS/ABBREVIATIONS

F	Force
h	Hour
kg	Kilogram
k	Rolling resistance coefficient
km	Kilometer
kW	Kilowatt
m	Meter
Nm	Newton-meter
N	Newton
rpm	Revolution per minute
s	Second
t	Time
T_c	Control Horizon
T_p	Prediction Horizon
V	Velocity
W	Watt
X	Distance
ʎ	Total rotational inertia constant
ro	Air density
δ	Sample Time
ACC	Adaptive Cruise Control
ADAS	Advanced Driving Assistance Systems
BEV	Electric Vehicle
BMS	Battery Management System
CC	Cruise Control
CDCS	Charge Depleting-Charge Sustaining
DP	Dynamic Programming
EV	Electric Vehicle

HVAC	Heating, Ventilation and Air Conditioning
ICE	Internal Combustion Engine
IM	Induction Machine
LCV	Light Commercial Vehicle
MPC	Model Predictive Control
Mo	Measured plant output
Mv	Manipulated variable
PHEV	Plug-in Hybrid Electric Vehicle
PID	Proportional-Integral-Derivative
PMP	Pontryagin’s Minimum Principle
Ref	Reference

1. INTRODUCTION

Fossil fuels are widely used in transportation sector especially in light duty vehicles and passenger cars. The latest research on the transportation sector has shown gas emissions corresponds 15% of the Europe's carbon dioxide emissions. Electricity as an energy source used for the vehicles engine systems offers renewable and environmental friendly energy in the transportation sector [1]. 'Tank-to-wheels' efficiency of the electric vehicles, which use electric power, is approximately three times more than the internal combustion engine vehicles [2]. Additionally, electric vehicle engines have less noise and vibration [3]. In spite of numerous advantages of electric vehicle, the number of electric vehicles in use is still insignificant.

The sales of electric vehicles had reached only 1% of the market shares in 2015. The reasons of this low use of electric vehicles are because of high battery costs, long charging time, low limited range, and limited charging infrastructures. The battery cost is in \$180/kWh to \$200/kWh range, which has been announced by GM and LG Chem. This cost has also been approved by the United States Department of Energy. Tesla and Panasonic also confirm these battery costs for electric vehicles [4]. When we consider the average battery size is around 40kW in the electric vehicle industry, battery prices for Battery Electric Vehicle (BEV) are a huge cost not only for suppliers but also for customers [5,6].

Long charging time is another research problem that electric vehicle manufacturers are trying to solve. The studies have shown that BEV is in fully charge to find 300 kilometers range in 20 minutes [7]. One of the famous electric vehicle manufacturer Tesla superchargers gives the opportunity to charge the battery fully in 20 minutes for Tesla Model S. The charger of BMW i3 EV is able to charge the 80 percent battery in approximately 30 minutes. However, this is still not enough time to satisfy the customer as like internal combustion engine vehicles tank filling [5,6].

Limited travelling range is also another research topic that researchers are currently working on [5,6]. Recently, average electric vehicle ranges increase to 350 kilometers with a single charge [6]. This number depends on used battery package size in vehicle. In small vehicle segment, Fiat 500e (2015) range is only 135 km range with 24 kWh battery. Chevrolet Spark EV (2015) has 130 km range in fully charge with 18.4 kWh battery energy. In medium large segment, Nissan Leaf (2016) serves 250 km range from 30kWh battery package. Tesla is one of the luxury EV segment manufacturer has increased the travelling range up to 480 km with enlargement battery packet up to 75kWh [8]. Statics show that most of vehicle customers want to use vehicles over 400 km range [6].

The physical electrical battery characteristic and battery power consumption of the vehicles directly affect the travelling range of electric vehicle. If there is large size battery used on vehicle and vehicle consumes low power consumption in moving, then this enlarges the electric vehicle travelling range automatically. Thus, the electric vehicle manufacturers have been trying to solve low travelling range problem by working on high capacity, and low weight batteries. Additionally, some other researchers are trying to find solutions to decrease vehicle battery consumption during the travelling on the road [9–12].

The high capacity and low weight batteries, and their management systems have previously been proposed to change electrical battery power consumption characteristics during travelling [9,10]. The ultra-capacitor usage theory on electric vehicle has previously shown to improve the vehicle performance [9]. Another development area is related with the battery management system (BMS) of the plug-in hybrid electric vehicle (PHEV), and electric vehicle (EV). Battery management system optimization methods are performed because of the variety of the BMS missions in vehicles (monitoring the capacity of the battery, remaining run-time information and counting charge-cycle etc.) [10]. The high technology battery management systems have shown to increase engine performance, and to extend the life of the battery [13].

Furthermore, new vehicle technologies such as regenerative braking systems and methodologies have also been integrated on vehicles to improve battery range [11,12]. The operation of induction machine (IM), which is behind the theory of regenerative braking system, is used to obtain the electric power from the powertrains when the brakes are applied. When the electric power is generated, then this power is sent to the battery to charge operation [11]. Methodological approaches are also defined to increase vehicle battery range during the conceptual phase electric vehicles by considering the vehicle technologies requirements such as heating, ventilation and air conditioning (HVAC) [12].

Autonomous driving technologies are another research area in the automotive industry. Advanced Driving Assistance Systems (ADAS) are improved on the vehicles to develop autonomous driving technology to improve road safety and driving comfort and also vehicle efficiency. Adaptive Cruise Control (ACC) is one of the important driver assistance systems that automatically adjust the vehicle speed to maintain a safe distance from the vehicles ahead. Adaptive Cruise Control (ACC), which directly controls engine or brake system working conditions, has also previously been used to increase the travelling range of the electrical vehicles [14,15].

ACC automatically adjusts the vehicle speed to maintain a safe distance from the front vehicles. Proportional-Integral-Derivative (PID), Linear Predictive Control and Model Predictive Control (MPC) methods have previously been used to set the speed, and the distance for ACC controllers to increase the travelling range of electrical vehicles [16–18]. Various control based eco-driving techniques, and solutions have also been developed to decrease battery consumption, and to increase battery range of EV and PHEV when ACC is active [16,19].

Meanwhile, numerical solutions with different optimal consumption algorithms have been proposed to decrease battery consumption, and to increase battery range of electric vehicle to obtain energy efficient ACC [15,19–23]. Pontryagin’s Minimum Principle (PMP), which is one of the optimization theories, is used to minimize the total energy consumption when maintaining a safe distance from vehicles ahead. Future trip information is a main parameter to evaluate the global optimum solution in PMP [16]. Another optimization problem solution is the use of model predictive control theory. In this theory, the quadratic equation of the optimization problem has been generated considering the economy performance, and safety index parameters [19]. Dynamic Programming (DP) according to Bellman is also used to guarantee energy efficiency using traffic signs or traffic data [15]. Charge Depleting-Charge Sustaining (CDCS) method, which is currently being used on the production vehicle, is another numerical method in the analysis of energy management strategies. An optimal control strategy based on Pontryagin’s Minimum Principle (PMP), and Charge Depleting and Sustaining (CDCS) method is used to compare the efficiency effect on plug-in hybrid electric vehicle (PHEV) or electric vehicle under different road conditions [20]. Additionally, information of the road profile and navigation systems is used to provide high efficient regenerative energy braking with different traffic conditions [21–23].

Various methods have been proposed to design energy efficient ACC to decrease battery consumption, and to increase battery range. However, to our knowledge, none of the previously proposed methods had evaluated the changes in the performance, and the power consumption of an electric vehicle when different controllers are used for ACC. The evaluation of performance directly effects the power consumption because if the vehicle needs more performance from the engine that means the vehicle consumes more electrical energy, which can simply be explained by the law of conversation of energy. Thus, energy efficiency of the electric vehicle should be evaluated by looking at the power consumption of the vehicle during travelling or standing. When the total energy that comes from the battery package is constant for one electric vehicle, then power consumption is a key parameter to assess energy efficiency of the electric vehicle. The assessment of power consumption can provide information about decrement/increment of the travelling range of electric vehicle. The aim of this thesis is to compare acceleration/deceleration performance, and power consumption of an electric vehicle when different controllers are used for ACC. The controller parameters on vehicle dynamics of the electric vehicle are varied to evaluate the performance, and the power consumption to obtain energy efficient ACC.

In this thesis, firstly lateral and longitudinal dynamic forces are analyzed to define dynamic model of the electric vehicle. The longitudinal forces are considered because of the minimal lateral force effect on the electric vehicle. Tractive force, aerodynamic resistance, acceleration force, gravitational force, and rolling resistance are included in the dynamic model of the electric vehicle. The mathematical model of the longitudinal motion dynamic of electric vehicle (LCV) is developed to include them into the cruise control and adaptive cruise control.

ACC is used to increase or decrease the vehicle speed to maintain a distance that is set from the driver. This scenario is used to evaluate energy efficiency of designed ACC systems in this thesis. Longitudinal acceleration and deceleration of the electric vehicle are simulated with different traffic conditions such as city or highway conditions. Experiments in MATLAB/Simulink environment are performed to evaluate acceleration/deceleration performance, and power consumption of the electric vehicle when different controllers

(PID, Fuzzy and MPC) are used for ACC. Since vehicle engine performance can be changed with the driving condition (smooth or aggressive), the energy efficiency of the system is evaluated by looking at the instantaneous vehicle power consumption.

The thesis is organized as follows. General architecture of the Cruise Control (CC) and Adaptive Cruise Control (ACC) that is developed for this thesis has been given in Chapter II. Then, the vehicle dynamic model of the electric vehicle, and power consumption model details are given in Chapter III. The details of the designed system with PID, Fuzzy and MPC controller are provided in Chapter IV. The experimental set-up, the scenario and the results that demonstrate how the performance and power consumption change when different controller parameters are used are given in Chapter V. The conclusion and future work of the proposed work are presented in Chapter VI.

2. GENERAL ARCHITECTURE

Cruise control (CC) system is an old vehicle technology that controls the vehicle speed to set the desired speed from the driver. CC system basically controls throttle-accelerator system of the vehicle engine system by comparing desired speed ($V_{desired}$), and actual speed of the vehicle (V_{actual}). CC system is turned on/off from set or resume switch which is typically placed on the steering wheel [24]. The block diagram of a cruise control system is shown in Figure 2.1.The aim of the CC is to reduce the error ($V_{desired}$ - V_{actual}), and send necessary torque command to the engine of the vehicle.

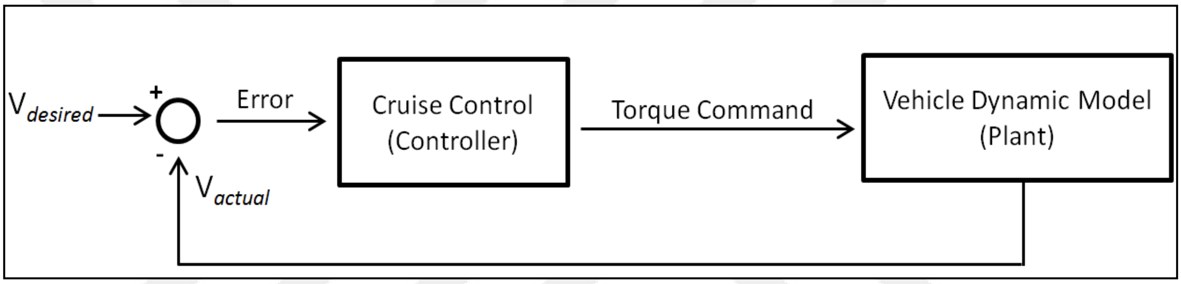

Figure 2.1. Cruise Control system configuration

Adaptive Cruise Control (ACC) is an intelligent form of CC that is basically developed from CC theory of speed limiting. However, apart from the CC, ACC system also controls the brake system of the vehicle. Driver does not have to adapt the speed of the vehicle considering the traffic conditions. The configuration of the Adaptive Cruise Control system is given in Figure 2.2. Sensors (radar or camera) are used in the front of the vehicle to detect conditions in the traffic. These sensors provide distance information (X_{real}-Real Distance) between vehicles, and any form presence in front of the vehicle to the ACC system controller. After all, ACC system controller automatically sets vehicle speed ($V_{desired}$) by looking at the information from sensor systems. If the distance between vehicle and any form is not in the critical range, the speed of the vehicle speed (V_{actual}) is set automatically to the desired speed that is set before. If the sensor systems in the vehicle detect any form, then the vehicle automatically slows down. This slowing down procedure continues until reaching safe distance ($X_{desired}$) between two vehicles. Desired speed and distance is controlled by ACC setting switches by the driver.

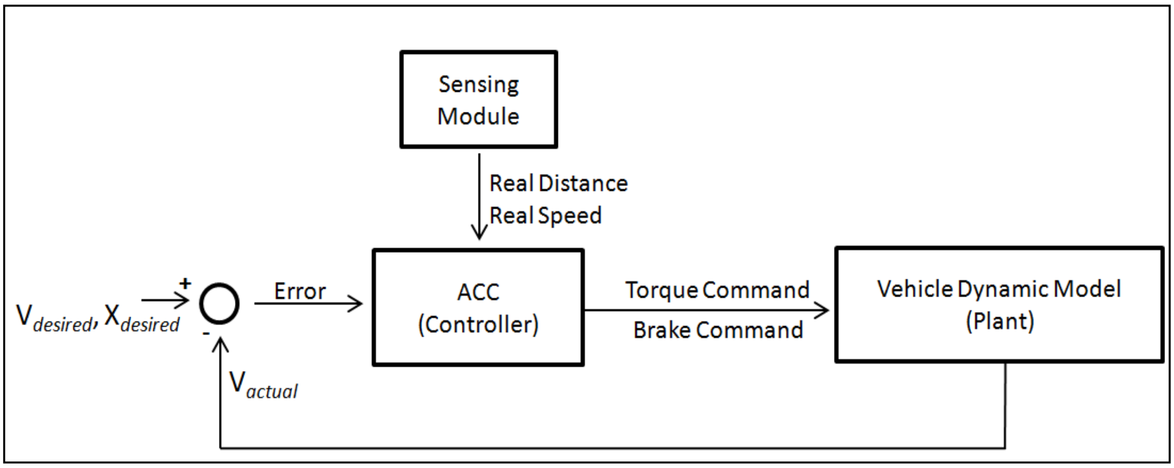

Figure 2.2. Adaptive Cruise Control system configuration

3. ELECTRIC VEHICLE DYNAMICS AND POWER CONSUMPTION MODELLING

Newton's second laws related forces are introduced to derive the electric vehicle dynamic model. There are two types of forces acting on the vehicle during motion, which are called longitudinal and lateral. Longitudinal forces on the electric vehicle are the traction force (F_{tr}), aerodynamic force (F_{aero}), rolling resistance (F_{rr}), gravitational force (F_g), and acceleration resistance (F_a) (Figure 3.1) [25–30]. Toe-in and suspension resistances are also the other longitudinal forces act on the electric vehicle. Lateral vehicle forces directly acts on the vehicle. Main lateral vehicle forces are cornering resistance, and lateral aerodynamic resistance. Toe-in, suspension effect and lateral forces are negligible thus these forces are not included in the dynamic equations of the electric vehicle used in this thesis.

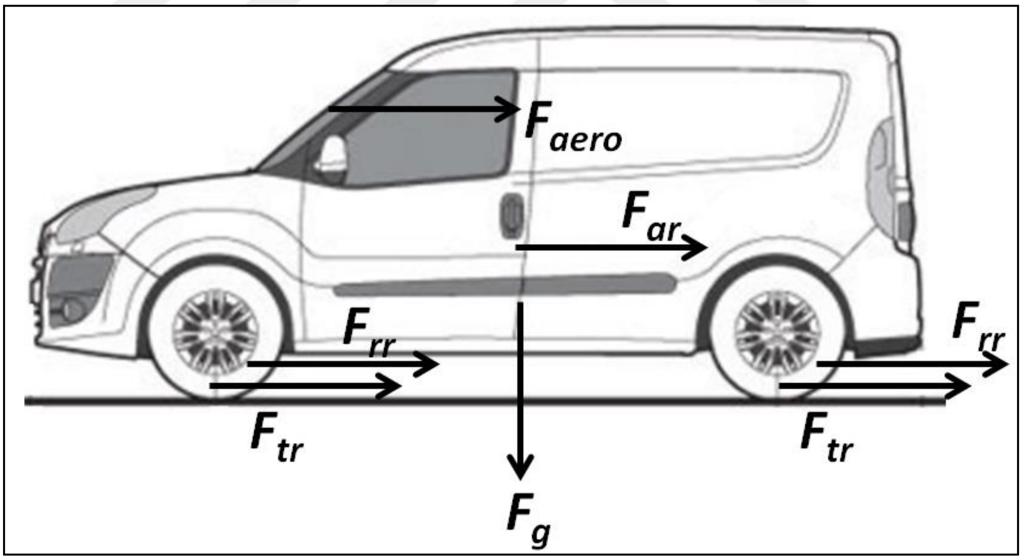

Figure 3.1. Longitudinal forces on vehicle

The general dynamic equation motion of the electric vehicle is given in Equation 3.1.

$$F_{tr}(\mathrm{t}) = m \times \frac{dV(t)}{d(t)} + F_{\mathrm{aero}} + F_{rr} + F_g + F_{ar} \tag{3.1}$$

where, m is mass of vehicle (kg) and V(t) is the vehicle speed (m/s).

The traction force is calculated as;

$$F_{tr}(\mathrm{t}) = \frac{E(t) \times n \times N_g \times N_a}{R} \tag{3.2}$$

where, E_t and n are engine net torque (Nm), and overall efficiency of power train (per cent), N_g is the total gear ratio of transmission, N_a is the driving axle ratio, and R is the effective tire radius (m). The tractive force input/output block is shown in Figure 3.2.

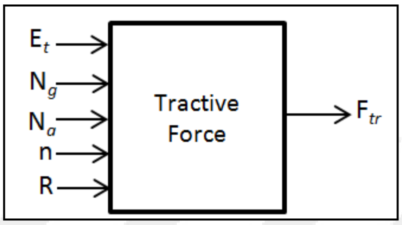

Figure 3.2. Tractive force input/output block

The aerodynamic force is calculated as follows;

$$F_{aero}(\mathrm{t}) = \frac{1}{2} \times \rho \times \mathrm{A_f} \times \mathrm{C_d} \times (\mathrm{V(t)} + \mathrm{V_w})^2 \tag{3.3}$$

where, ρ represents air density, A_f is the maximum vehicle frontal cross area (m^2), C_d is the drag coefficient, V(t) is the vehicle speed (m/s), and V_w is the wind velocity (m/s). The aerodynamic force input/output block is given in Figure 3.3.

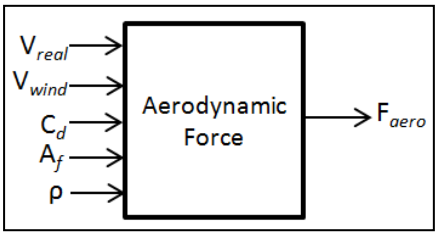

Figure 3.3. Aerodynamic force input/output block

The rolling resistance is defined as follows;

$$Frr = k \times W \times cos\,\theta \tag{3.4}$$

where, k shows rolling resistance coefficient (N/kg), W is multiply of the mass of vehicle (m) (kg) and gravitational acceleration (g) (m/s^2), and θ is the angle of incline. The rolling resistance input/output block is shown in Figure 3.4.

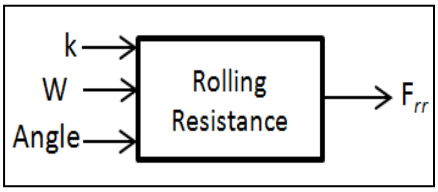

Figure 3.4. Rolling resistance input/output block

The gravitational resistance is calculated as follows with same parameter of Frr;

$$Fg = m \times g \times \sin\theta \tag{3.5}$$

The gravitational resistance input/output block is given in Figure 3.5.

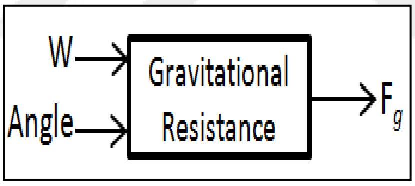

Figure 3.5. Gravitational resistance input/output block

The acceleration resistance is calculated as;

$$\mathrm{F_{ar}} = \lambda \times \mathrm{m} \times \frac{\mathrm{dV(t)}}{\mathrm{d(t)}} \tag{3.6}$$

where, λ is rotational inertia constant, m is mass of vehicle (kg), and V(t) is the vehicle speed (m/s). The acceleration resistance input/output block is given in Figure 3.6.

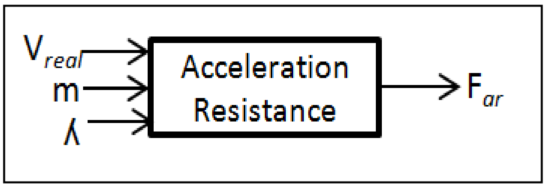

Figure 3.6. Acceleration resistance input/output block

3.1. PARAMETERS OF THE ELECTRIC VEHICLE

The electrical vehicle parameters that are used in this thesis are taken from a vehicle company in Turkey. The parameters of this vehicle are given in Table 3.1.

Table 3.1. Vehicle model parameters

		Value
General Parameters	Vehicle speed, V (m/s)	Variable
	Mass of vehicle, m (kg)	1705
	Gravitational acceleration, g (m/s^2)	9,81
	Angle of incline, θ	Variable
Traction Force Parameters	Engine net torque, E_t (Nm)	255
	Overall efficiency of powertrain, n (per cent)	92
	Total gear ratio of transmission, N_g	9,99
	Driving axle ratio, N_a	1 to 1
	Effective tire radius, R_{eff} (m)	0,32
Aerodynamic Force Parameters	Air density, ro	1,225
	Max vehicle frontal cross area, A (m^2)	2,66
	Drag coefficient, C_d	0,302
	Wind velocity, V_w	Variable
Rolling Resistance Parameters	Rolling resistance coefficient, k (N/kg)	0,011
Acceleration Resistance Parameters	Total rotational inertia constant, ϗ	1,17

It can be seen from Equation 3.2 that F_{tr} directly depends with E_t. Generally, when the engine speed-engine torque behavior of electric motor is analyzed, it is noticed that the torque parameter is not same for every engine speed interval. The electric vehicle motor characteristic of the electric vehicle is modeled using the engine characteristics graph given in Figure 3.7. It can be seen from Figure 3.7 that when the engine rpm increases then the engine peak torque starts to decrease after 4500 rpm interval.

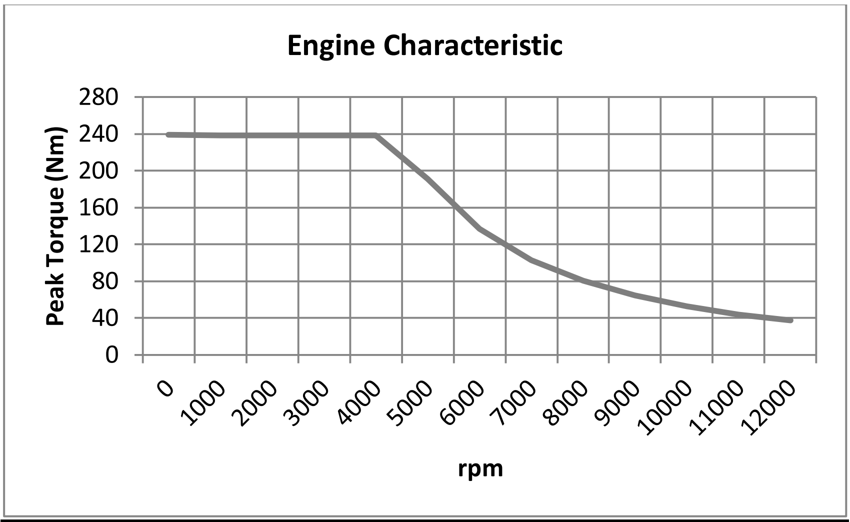

Figure 3.7. EV engine characteristic

The engine torque parameter is the main parameter that affects the vehicle as a tractive force. Thus, the torque-speed characteristic is formalized to include ACC function into electric vehicle used. The mathematical representation of electric vehicle engine characteristics is done by Curve Fitting Tool of MATLAB [31] using the engine characteristic given in Figure 3.7. Curve Fitting Tool configuration interface can be seen in Figure 3.8 regarding work. In this study, Gaussian method is used with '2' number of terms chosen as a fitting method to derive the mathematical representation, and the following equation is obtained:

$$\mathrm{F(x)} = \mathrm{a}_1 \times e^{\left(-\left(\frac{\mathrm{x}-\mathrm{b}_1}{\mathrm{c}_1}\right)\right) \times \left(-\left(\frac{\mathrm{x}-\mathrm{b}_1}{\mathrm{c}_1}\right)\right)} + \mathrm{a}_2 \times e^{\left(-\left(\frac{\mathrm{x}-\mathrm{b}_2}{\mathrm{c}_2}\right)\right) \times \left(-\left(\frac{\mathrm{x}-\mathrm{b}_2}{\mathrm{c}_2}\right)\right)} \tag{3.7}$$

where F(x) is the peak torque, and x is the engine rpm. The coefficients are calculated as a_1=86.71, a_2=385.6; b_1=3744, b_2=-9801; c_1=2219 and c_2=14080.

Equation 3.7 is used to provide the real torque to the electric engine by looking at the actual engine speed. Torque and maximum vehicle speed are directly limited by engine speed value because $\mathrm{E_t}$ is not a flat function, and it changes with engine speed.

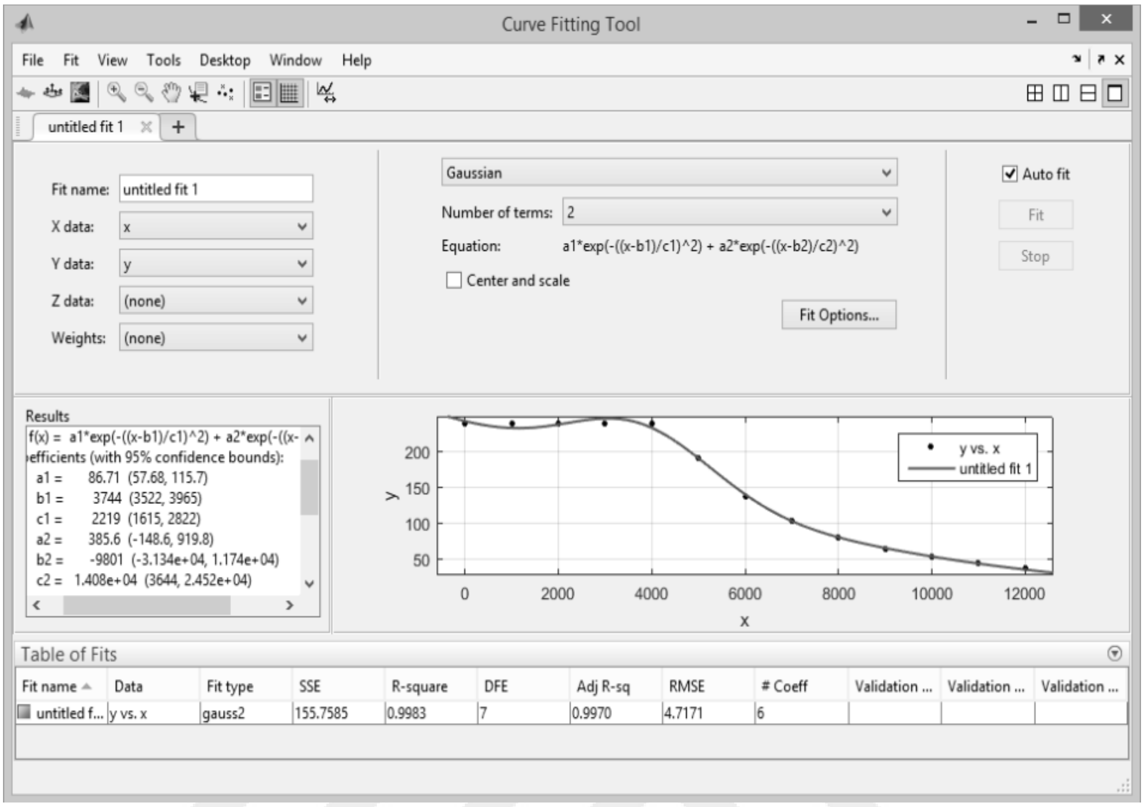

Figure 3.8. Electric vehicle engine characteristics modeling (rpm/torque)

3.2. POWER CONSUMPTION MODELING

Power consumption is the parameter that is used to evaluate ACC model. The required power formula is written in Equation 3.8 and 3.9 using physical laws to generate tractive force in Equation 3.1. In Equation 3.8 and 3.9, the total power requirement (P_{total}) [W] at each time step (second) is estimated from the sum of all resistive forces multiplied by the vehicle's longitudinal speed [32–36].

$$P_{total} = F_{tr} \times V = \left(F_a + F_{aero} + F_{rr} + F_g + F_{ar}\right) \times V \tag{3.8}$$

where, F_{tr} is traction force (N), V is vehicle speed (m/s), F_a is acceleration force (N), F_{aero} is aerodynamic force (N), F_{rr} is rolling resistance (N), F_g is gravitational force (N) and F_{ar} is acceleration resistance (N). When all equations from 3.1 to 3.6 are inserted in Equation 3.8 then the following equation is obtained.

$$P_{total} = \left(\left(m \times \frac{dV(t)}{d(t)}\right) V + \left(\frac{1}{2} \times \rho \times A_f \times C_d \times (V(t) + V_w)^2\right) V + (k \times W \times \cos\theta) V + (m \times g \times \sin\theta) V + (\lambda \times m \times \frac{dV(t)}{d(t)}) V\right) \quad (3.9)$$

where, m shows mass of vehicle (kg), V represents vehicle speed (m/s), ρ is air density, A_f is maximum vehicle frontal cross area (m^2), C_d is drag coefficient, V_w is wind velocity (m/s), k is rolling resistance coefficient (N/kg), W is multiply of the mass of vehicle (m) (kg) and gravitational acceleration (g) (m/s^2), θ is angle of incline and λ shows rotational inertia constant.

4. DESIGN OF AN ADAPTIVE CRUISE CONTROL (ACC) USING DIFFERENT CONTROLLERS

ACC is designed with three well-known controllers that are Proportional-Integral-Derivative (PID), Fuzzy and Model Predictive Controller (MPC) to evaluate their impact on vehicle dynamic regarding acceleration/deceleration performance, and power consumption. In this section, initially, theoretical information behind these controllers is given, and then the details of each ACC design with these three controllers are provided.

4.1. DESIGN OF ACC USING A PID (PROPORTIONAL-INTEGRAL-DERIVATIVE) CONTROLLER

Proportional-Integral-Derivative (PID) controller is a well-known controller used in many areas such as automation systems for energy production, transportation, and manufacturing [37]. The aim of the PID controller is to minimize the error (the difference between the target value (F_{tr}) and feedback value of what is controlled). A typical mathematical representation of a PID control system is given as follows

$$u(t) = K_p \left[e(t) + \frac{1}{K_i} \int e(\tau) d(\tau) + K_d \frac{de(t)}{d(t)} \right] \quad (4.1)$$

Error signal $e(t)$ is used to generate proportional, integral and derivative actions on the input signal $u(t)$. The error signal $e(t)$ is defined as $e(t) = r(t) - y(t)$, $r(t)$ is the reference input signal and $y(t)$ is the output signal of the system [38]. In this equation, K_p represents proportional gain, K_i is the integration gain and K_d is the derivative gain.

The ACC with a PID controller for the electric vehicle is shown in Figure 4.1. In this model, PID controller automatically generates the proportional, integral and derivative actions on the error signal. The error signal means the difference between desired tractive force and real tractive force in this thesis. PID controller sends 'F_{net}' to the vehicle dynamic system by controlling this error value.

Desired engine force comes from "ACC decision block". ACC decision block calculates the desired tractive force by checking radar sensor value, and driver set speed value ($V_{desired}$). Driver set speed value is a cruising value for ACC decision block. If any object is detected in front of the vehicle from detection sensors, then ACC decision block automatically change desired value into the detection form speed ($V_{detected}$). If there is no object detected in front of the vehicle, then ACC decision block set desired value to driver cruising value again.

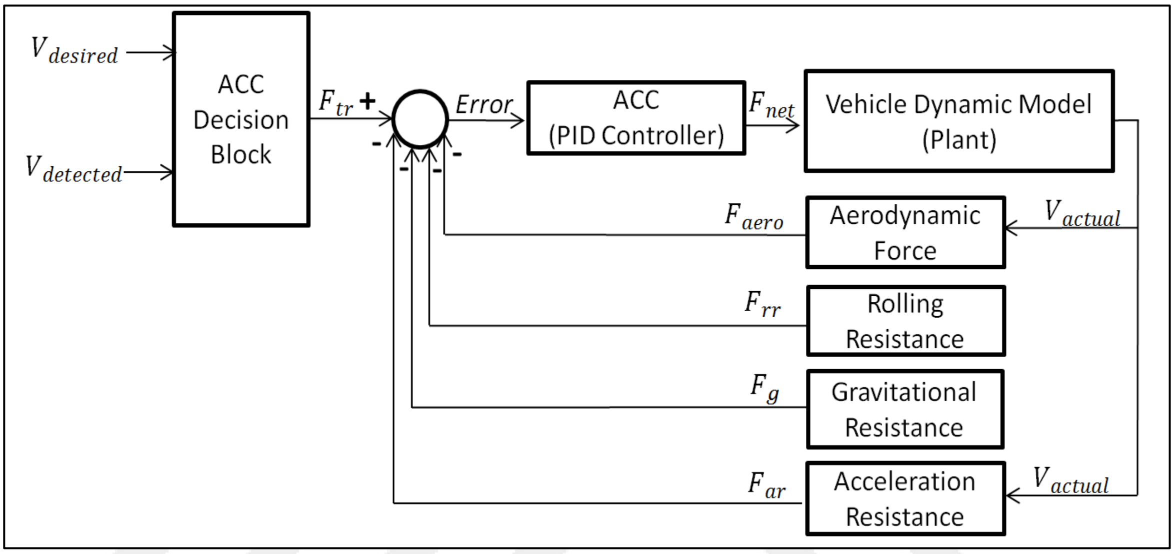

Figure 4.1. Adaptive Cruise Control system with PID controller

4.2. DESIGN OF ACC USING A FUZZY CONTROLLER

Fuzzy control systems are composed of four main elements, which are i) a set of “If-Then rules” that contains a linguistic description of how to achieve control, ii) “fuzzy inference“ that is the decision making assumptions from experience and experiment knowledge about how best to control the plant, iii) “fuzzification mechanism” that is the process to convert controller inputs into one or more fuzzy sets, and iv) “defuzzification mechanism” that converts the fuzzification sets into the final output sets according to “If-Then rules” and “fuzzy inference”[39]. This operation flow is given in Figure 4.2. In this operation flow, Fuzzy controller use membership function, input and output ranges rules for each operation modes from input to output.

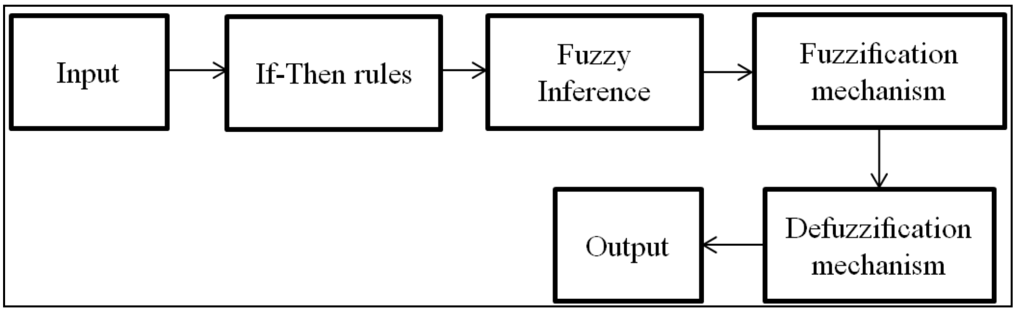

Figure 4.2. Fuzzy operation workflow

The ACC with a Fuzzy controller for the electric vehicle is shown in Figure 4.3. In fuzzy controller, traction force (F_{tr}) is not controlled directly by looking at the desired and actual engine force. In this model, Fuzzy Logic Controller looks at the desired and actual speed of the vehicle to give according engine force into the system. MATLAB/Simulink Fuzzy Logic Designer program interface used in this thesis is given in Figure 4.4. "ACC Decision Block" is the desired speed decision mechanism, which directly looks at sensor information, and sets speed from driver. For example, when driver sets the cruising speed to a 90 km/h, this block provides 90 km/h speed information as an output (V_{cal}) if no vehicle or any object is presence in front of the vehicle. If there is a vehicle or any object is detected in front of the vehicle, then ACC decision block gives detected speed to decelerate the vehicle. After all, "ACC decision block" output, and "actual vehicle speed from the vehicle" difference are given to the Fuzzy controller as an input. Fuzzy controller decides traction force level by looking at the rules that are introduced in "fuzzy inference".

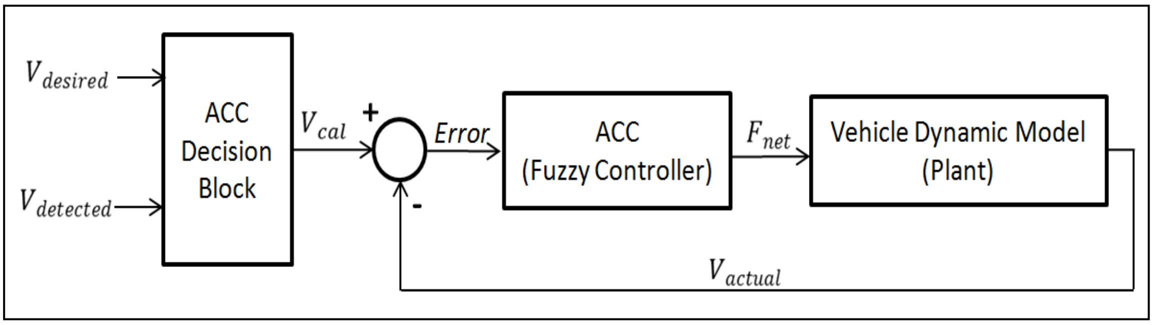

Figure 4.3. Adaptive Cruise Control system with Fuzzy controller

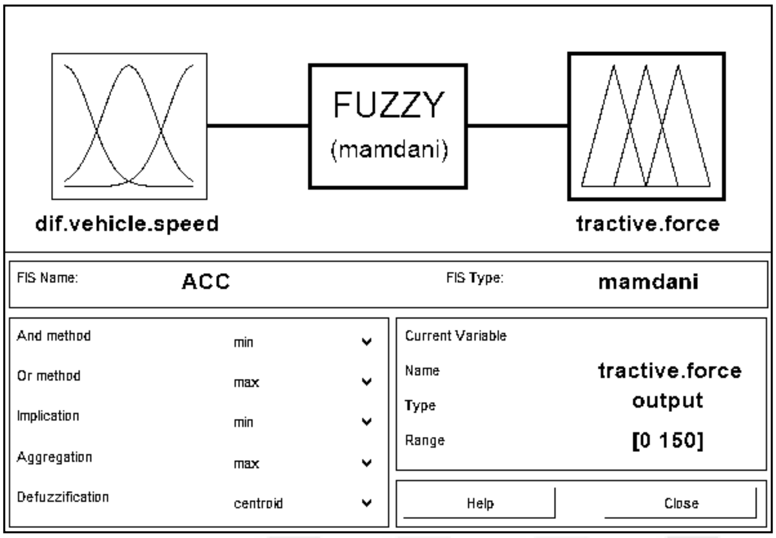

Figure 4.4. Fuzzy Logic designer interface on Simulink

4.3. DESIGN OF ACC USING A MODEL PREDICTIVE CONTROLLER (MPC)

Model Predictive Control (MPC) is based on solving an optimization problem numerically at each time step with considering some constrains [40,41]. In recent years, the advances in MPC algorithms, and design processes are also discovered in automotive area to increase efficiency of the vehicle system, and electronic components. MPC is widely used in power train and chassis control applications in the automotive industry [42]. In this thesis, MPC is used because of its advantages in terms of efficiency and accuracy.

In MPC theory, there are three main input and output component. Measured plant output (mo) and references (ref) are the input parameters. Model predictive controller gives an output as manipulated variable by looking at these two inputs. Prediction, control horizon and sample time are used by MPC when calculating output value from input value (Figure 4.5).

In ACC design, V_{cal} is calculated from “ACC decision block”. MPC controller calculates traction force (F_{tr}) by managing three parameters that are “measured plant output”, “reference” and “manipulated variable”. Output (V_{cal}) of the “ACC decision block” provides reference (ref) value for the MPC controller. Measured plant output (mo) (V_{actual}) is speed signal that is a feedback from the vehicle. The manipulated variable (mv) is the controller block output (F_{net}) that is tractive force value expressed in Newton. MPC controls the traction force directly by looking at the desired, and actual vehicle speed (Figure 4.6).

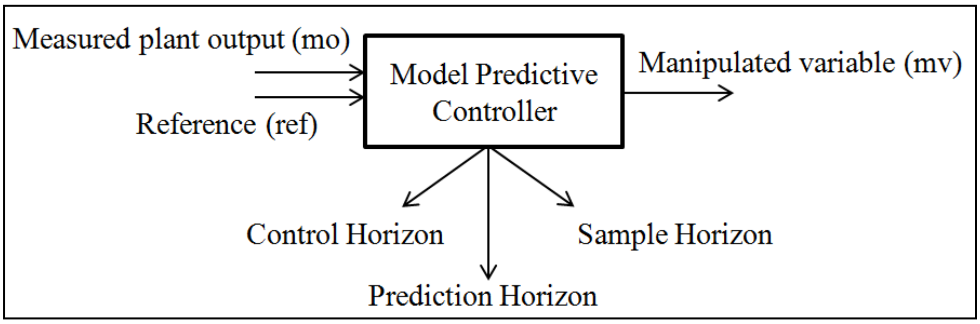

Figure 4.5. Model Predictive Controller working principle

In ACC design, V_{cal} is calculated from "ACC decision block". MPC controller calculates traction force (F_{tr}) by managing three parameters that are "measured plant output", "reference" and "manipulated variable". Output (V_{cal}) of the "ACC decision block" provides reference (ref) value for the MPC controller. Measured plant output (mo) (V_{actual}) is speed signal that is a feedback from the vehicle. The manipulated variable (mv) is the controller block output (F_{net}) that is tractive force value expressed in Newton. MPC controls the traction force directly by looking at the desired, and actual vehicle speed (Figure 4.6).

Model predictive controller configuration is directly set using MPC Designer APP in MATLAB/Simulink [43]. Initially, plant is linearized and introduced into the MPC controller. Then, optimization methods, control, prediction horizon and sample time are selected (Figure 4.7). Later, ACC controller is developed to control the performance of the electric vehicle.

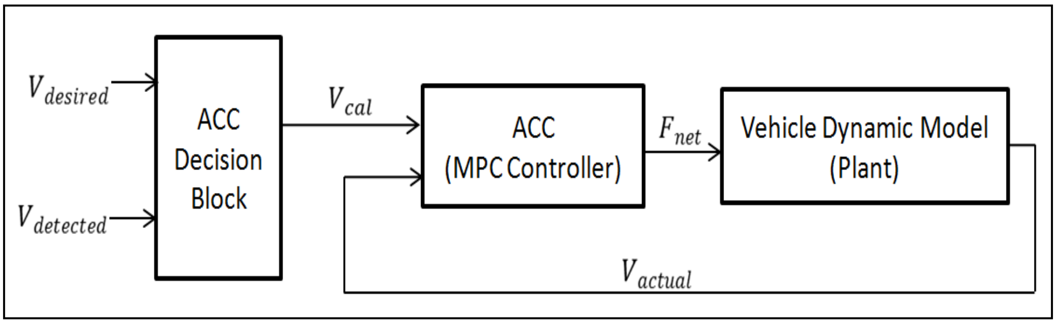

Figure 4.6. Adaptive Cruise Control system with MPC controller

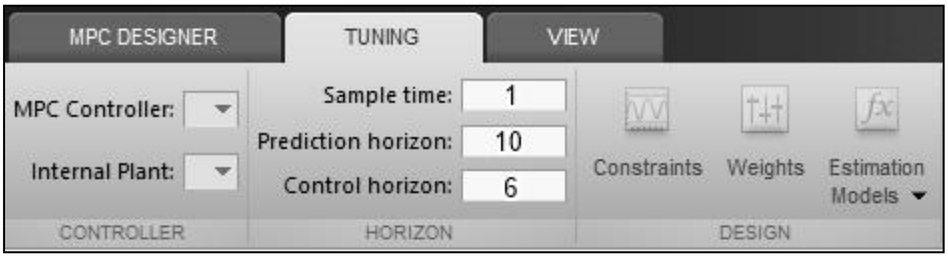

Figure 4.7. MPC Designer interface in MATLAB/Simulink

5. EXPERIMENTS AND RESULTS

In this thesis, the simulation experiments were done using MATLAB/Simulink [44] tool. All modeling equations that were given in Section 3.1 and 3.2 were implemented in MATLAB/Simulink [44].

Firstly, vehicle dynamic conditions and ACC function with PID controller is modeled by MATLAB/Simulink[45] tuning tool. ACC decision block, PID controller, dynamic vehicle longitudinal forces and sensor information (vehicle detected or no vehicle) are the main blocks in this model. All blocks can be seen from Figure 5.1.

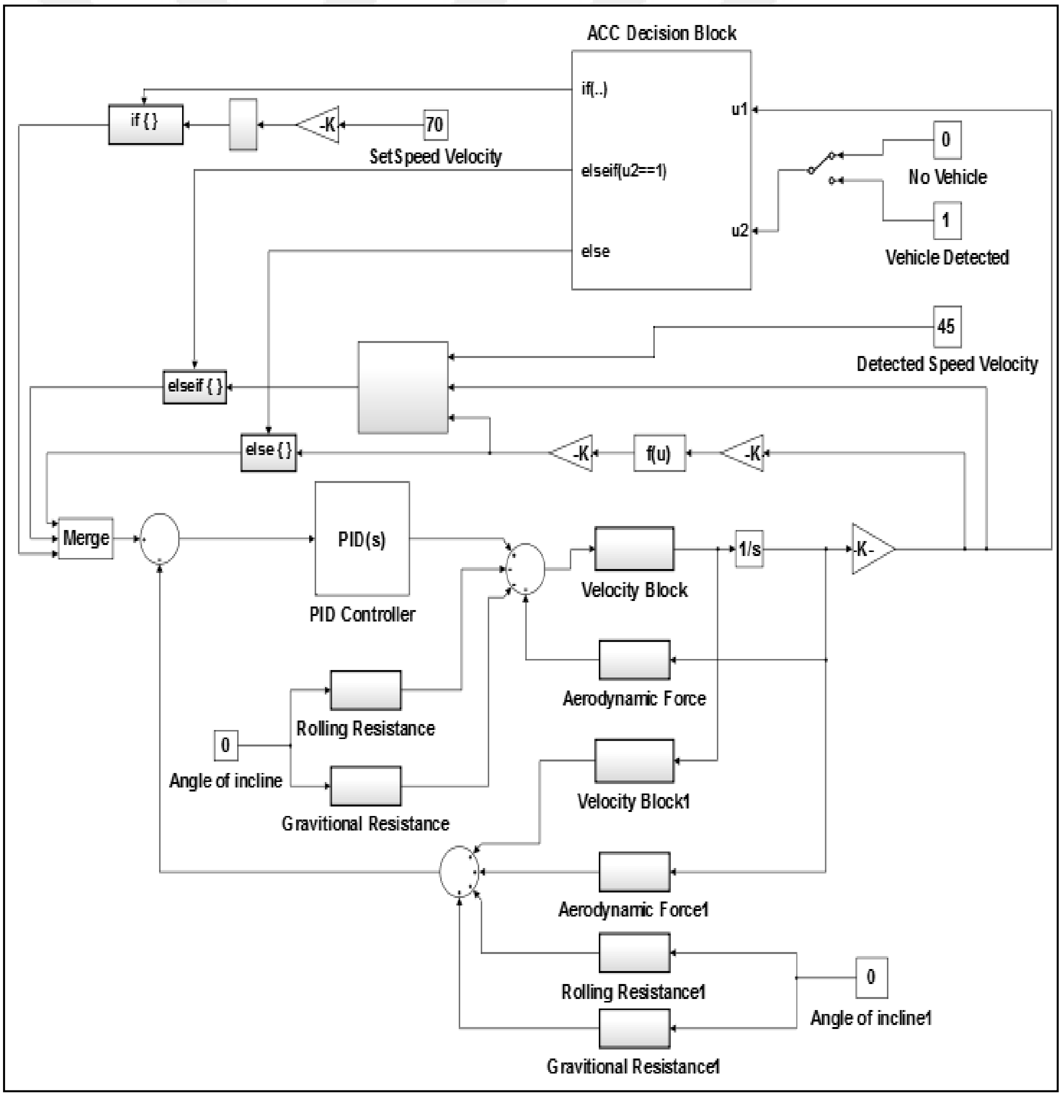

Figure 5.1. ACC model with PID in MATLAB/Simulink

Secondly, ACC model with ACC decision block, Fuzzy controller, dynamic vehicle longitudinal forces and sensor information (vehicle detected or no vehicle) is created in MATLAB/Simulink [51] tuning tool that is given in Figure 5.2.

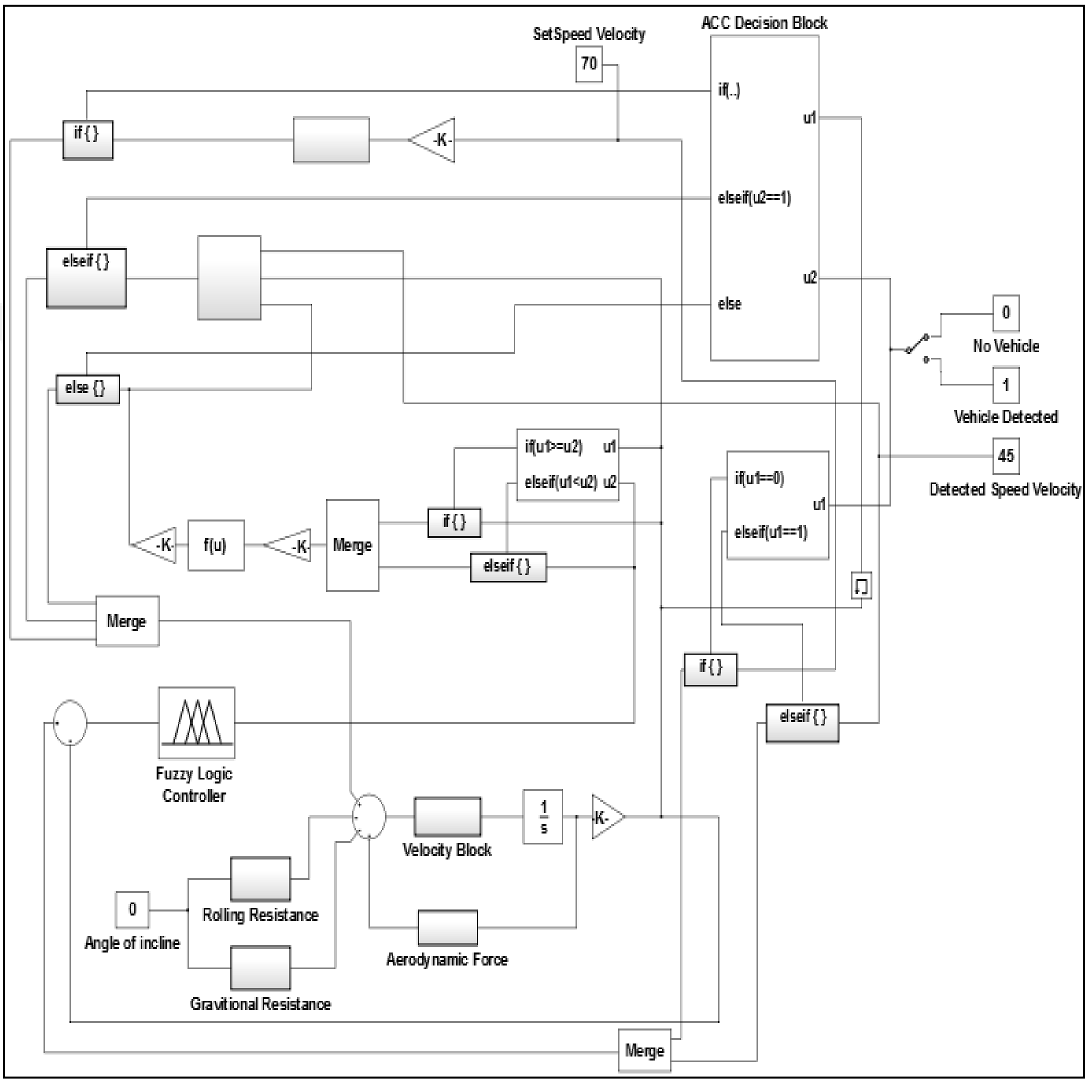

Figure 5.2. ACC with Fuzzy Logic Controller in MATLAB/Simulink design

As a final model, vehicle longitudinal motion forces and ACC with Model Predictive Controller (MPC) configuration are implemented in MATLAB/Simulink [43]. Relationship between ACC decision block, dynamic vehicle longitudinal forces and sensor information is given in Figure 5.3.

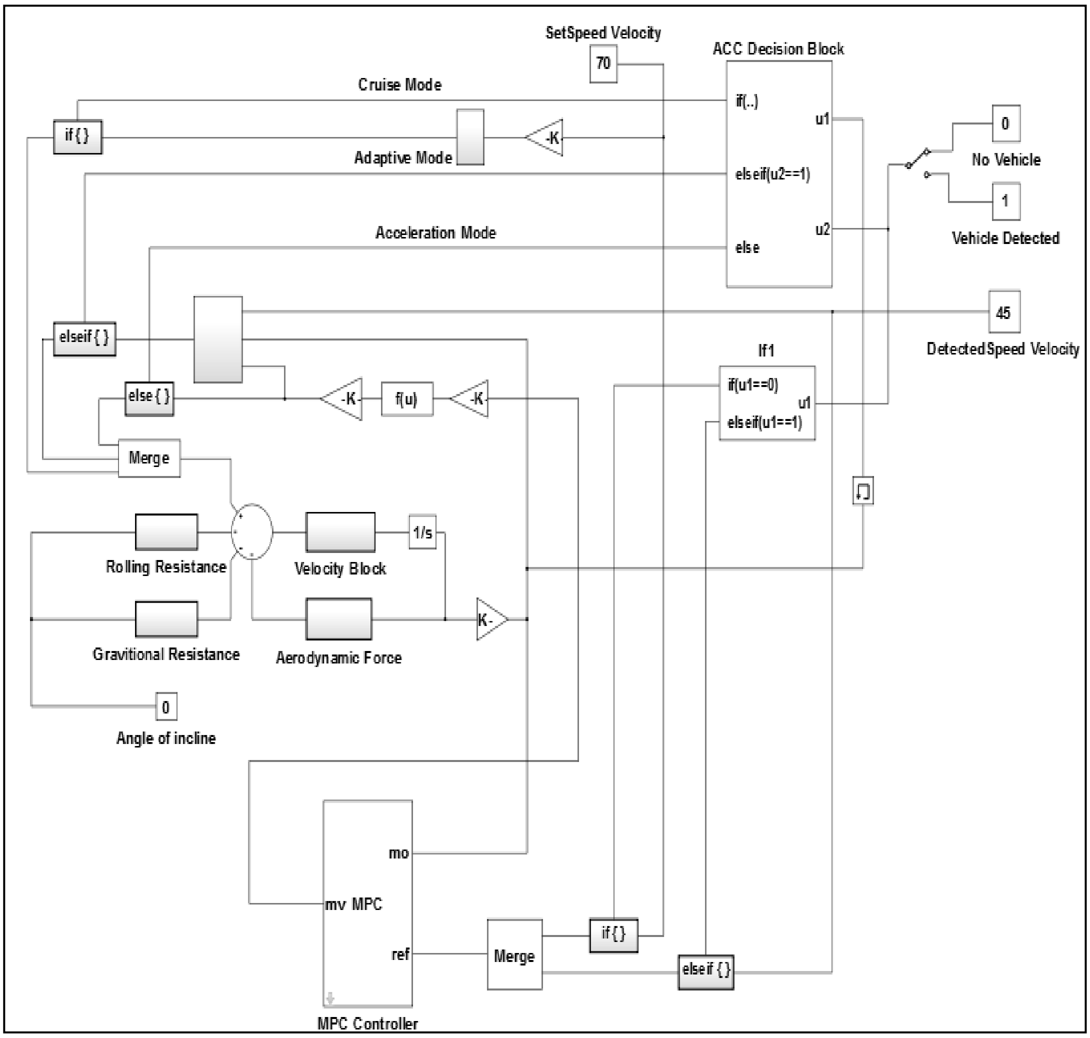

Figure 5.3. ACC with Model Predictive Controller in MATLAB/Simulink design

A scenario was selected to evaluate the performance in acceleration/deceleration, and power consumption when ACC system was designed with three different controllers (PID, Fuzzy and MPC). In the scenario, the driver set the cruising speed to 70 km/h. Initially; there was no vehicle or object detected in front of the vehicle. After the vehicle reached the desired speed, then an object which had a speed between 40 to 45 km/h interval was detected by the sensing module. ACC decision block sent a signal to the engine system to decelerate. Engine system was also chosen as a deceleration mechanism to charge the electric vehicle battery. Then, when the road was clear (no vehicle in the front), ACC decision block started to accelerate the vehicle back to the driver cruising value by sending speed-up comment to the ACC controller. The same scenario had been evaluated using PID, Fuzzy and MPC controllers in ACC.

5.1. PID CONTROLLER PARAMETERS EFFECTS ON ACC SYSTEM BEHAVIOR AND EFFICIENCY

The choice of PID controller gain parameters was important because they had an effect on ACC dynamic system, which had been described in Section 4.1. In this part, MATLAB/Simulink PID [45] tuning tool had been used to decide the PID gains. In the first case, P, I, D and N parameters were selected for two different models (Table 5.1). It was noticed that the transient behavior was aggressive (not robust) at disturbance rejection in both models. The response time was faster in the first model than the second model. It could be noticed that the vehicle reached the desired speed faster when the first model were used (Figure 5.4). However, the vehicle speed settled to 70 km/h faster when the second model was used. Power consumption of the battery was more when there was a fast acceleration feedback, and longer settling time. The power consumption of two models under the same condition could be seen in Figure 5.5. In deceleration phase, first model behaved more efficient because of the fast regeneration of the battery.

Table 5.1. First and second PID model parameters

	First Model	**Second Model**
PID Parameters	**Value**	**Value**
P	0	0.1654
I	0.6699	0.0003
D	0	-2.35
N	100	0.080
Response Time Behavior	Faster	Slow
Transient Behavior	Aggressive at disturbance rejection	Aggressive at disturbance rejection

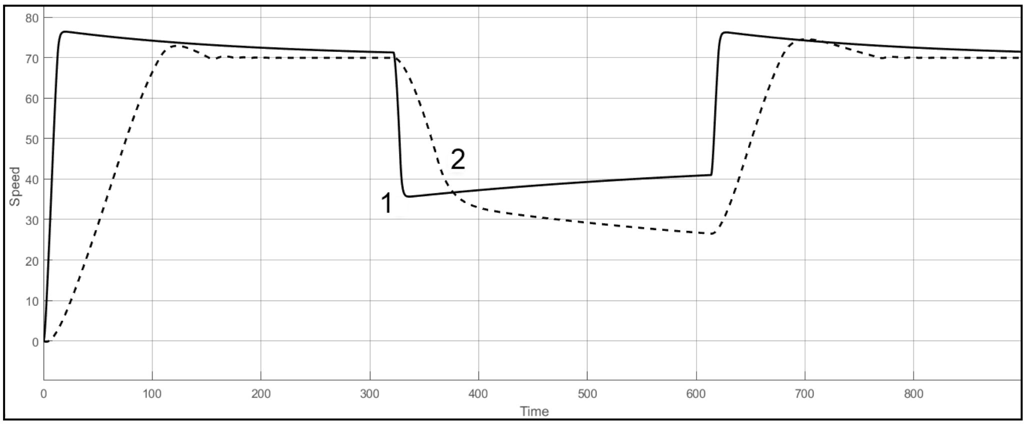

Figure 5.4. First and second PID systems effect on vehicle speed (km-h/s)

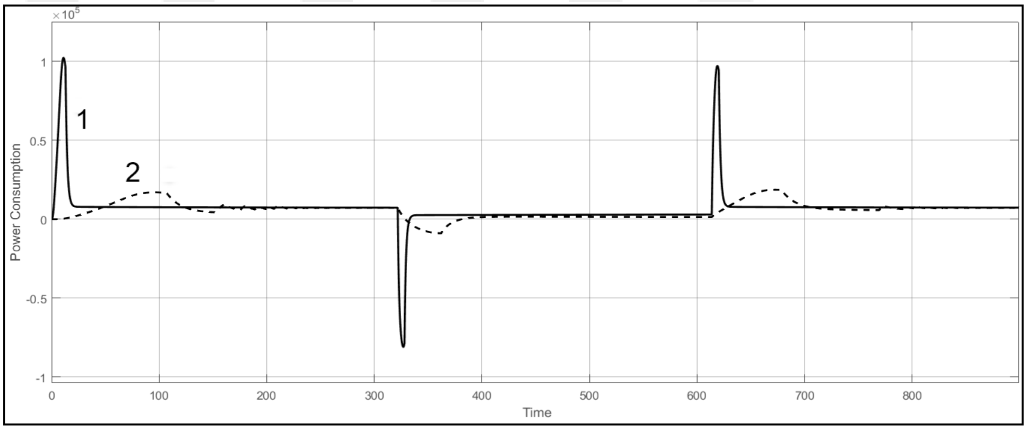

Figure 5.5. First and second PID systems effect on power consumption (W/s)

Then the controller performance had been evaluated when the filter coefficient effect (N) had been changed. The second model filter coefficient was changed from 0.080 to 0.070 (Table 5.2). It was observed that hanging filter coefficient created the ripples on the vehicle speed (Figure 5.6). Thus, speed could not be kept constant because of these ripples. Additionally, these ripples could cause extra power consumption for the vehicle (Figure 5.7). As a summary, when the filter coefficient (N) was decreased, vehicle acceleration and deceleration phase and also steady state behavior oscillation frequency was increased and caused energy battery efficiency of the vehicle in worst direction.

Table 5.2. Second and third PID model parameters

	Second Model	Third Model
PID Parameters	**Value**	**Value**
P	0.1654	0.1654
I	0.0003	0.0003
D	-2.35	-2.35
N	0.080	0.070
Response Time Behavior	Slow	Slow
Transient Behavior	Aggressive at disturbance rejection	Aggressive at disturbance rejection

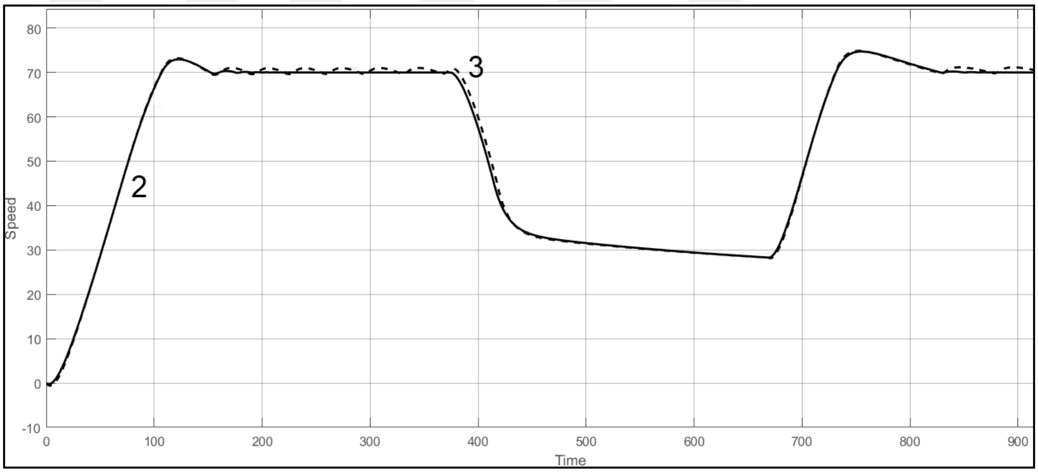

Figure 5.6. Second and third PID systems effect on vehicle speed (km-h/s)

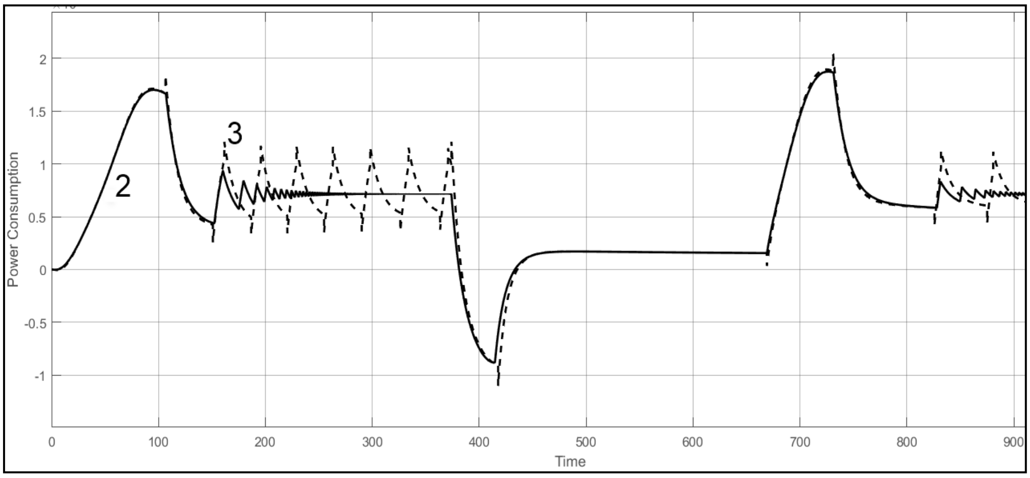

Figure 5.7. Second and third PID systems effect on power consumption (W/s)

Another control parameters had been used for the fourth model (Table 5.3). Closed loop response time behavior was selected same for both models. First model transient behavior was set as more aggressive at disturbance rejection than fourth model by changing P, I, D and N parameters. It was observed that speed transient behavior was smoother in fourth model than first model (Figure 5.8). First ACC model consumed much power than fourth model when ACC system was in acceleration period (Figure 5.9).

Table 5.3. First and fourth PID model parameters

	First Model	**Fourth Model**
PID Parameters	**Value**	**Value**
P	0	0.1469
I	0.6699	0.6188
D	0	-0.1841
N	100	0.798
Response Time Behavior	Faster	Faster
Transient Behavior	More aggressive at disturbance rejection	More robust against plant uncertainty

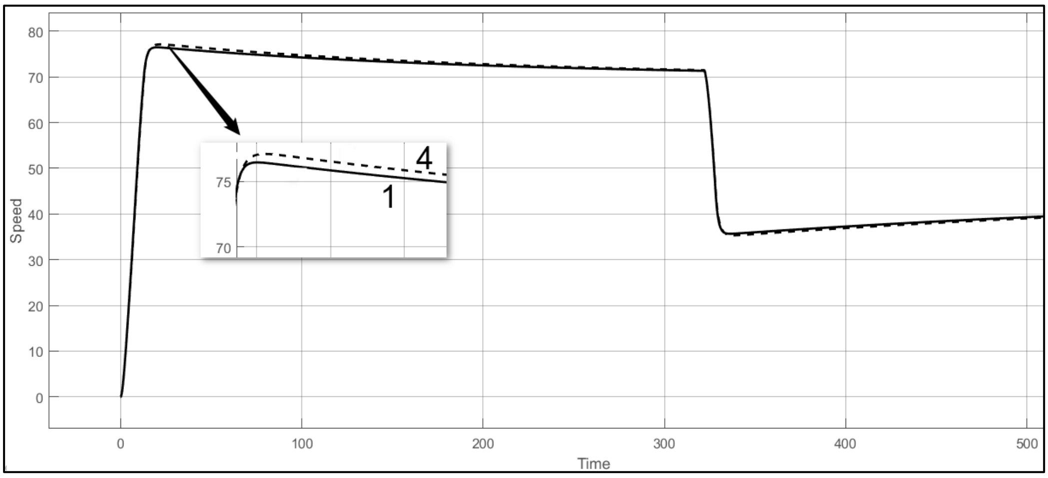

Figure 5.8. First and fourth PID systems effect on vehicle speed (km-h/s)

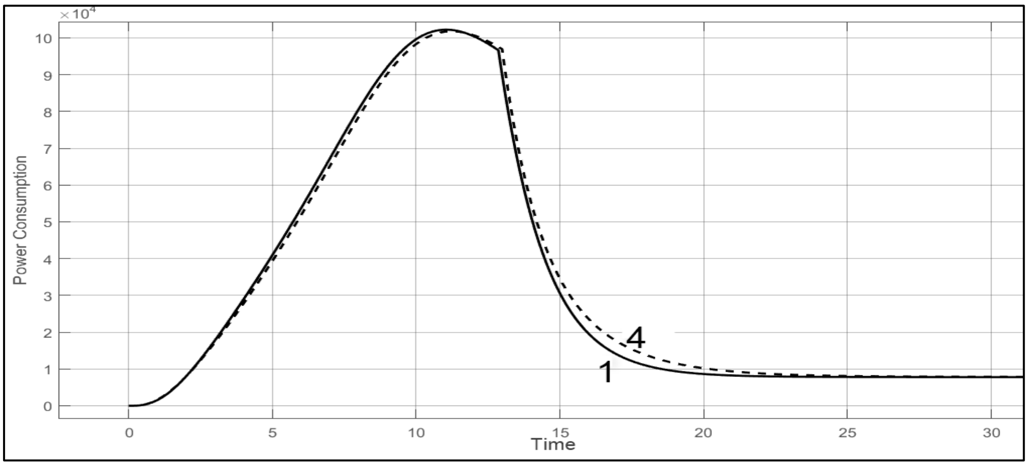

Figure 5.9. First and fourth PID systems effect on power consumption (W/s)

5.2. FUZZY CONTROLLER PARAMETERS EFFECTS ON ACC SYSTEM BEHAVIOR AND EFFICIENCY

Fuzzification, fuzzy inference process and defuzzification are three important steps to design fuzzy controller. The purpose of fuzzification is to map the inputs to the values 0 to 1 using membership functions. At this stage, membership functions can be triangular, trapezoidal, linear, gaussian etc. After the fuzzification stage, fuzzy rules are set in fuzzy inference process. In fuzzy theory, Mamdani and Takagi-Sugeno are two commonly linguistic form rules as fuzzy inference process. Once and for all, the output from the inference engine are converted into crisp output value with defuzzification methods. Common defuzzification techniques are center of-area (gravity), center-of-sums and mean of maxima [46–48].

Different membership functions were compared on the same ACC operation condition. Input and output range effects were investigated to understand fuzzification, and defuzzification process effect on power consumption. In this thesis, Mamdani inference approach was used because of the nonlinear ACC behavior.

Fuzzy parameters for two different models were given in Table 5.4. Both the model input and output Fuzzy range were the same. However, first membership function was chosen as a z-shape, and second membership function was chosen as a triangular-shaped. Fuzzy model input range was selected as [-150, +150] in negative and positive interval because if the vehicle needed to slow down fuzzy input became in negative interval. However, if the vehicle was in speed up, fuzzy input became in positive interval (as it had been shown in Figure 4.3). [-150, +150] interval was selected with considering minimum and maximum vehicle speed difference coming from the closed loop feedback. Output interval of fuzzy logic was directly related with engine force. It was observed that vehicle speed transient behavior was more aggressive when zmf membership function was used. Furthermore, the settling time of first model was shorter than second model (Figure 5.10). Power consumption of the battery was more in the first model because of the fast acceleration feedback (Figure 5.11). However, because of the negative torque effect, first model generated more energy in short deceleration interval than second model.

Table 5.4. First and second Fuzzy models parameters

Fuzzy Models	**First Model**	**Second Model**
Input Range	[-150,+150]	[-150,+150]
Input Membership Function Type	zmf	trimf
Output Range	[0,+150]	[0,+150]
Ouput Membership Function Type	zmf	trimf

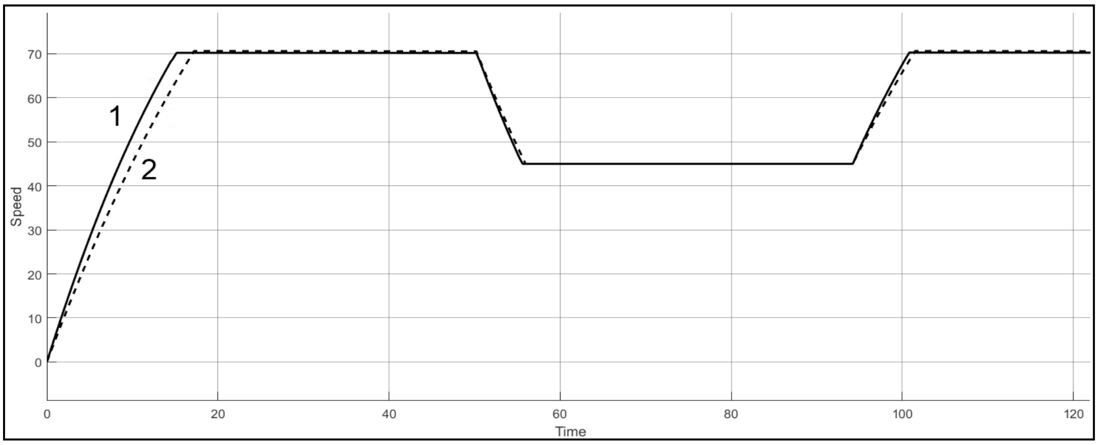

Figure 5.10. First and second Fuzzy systems effect on vehicle speed (km-h/s)

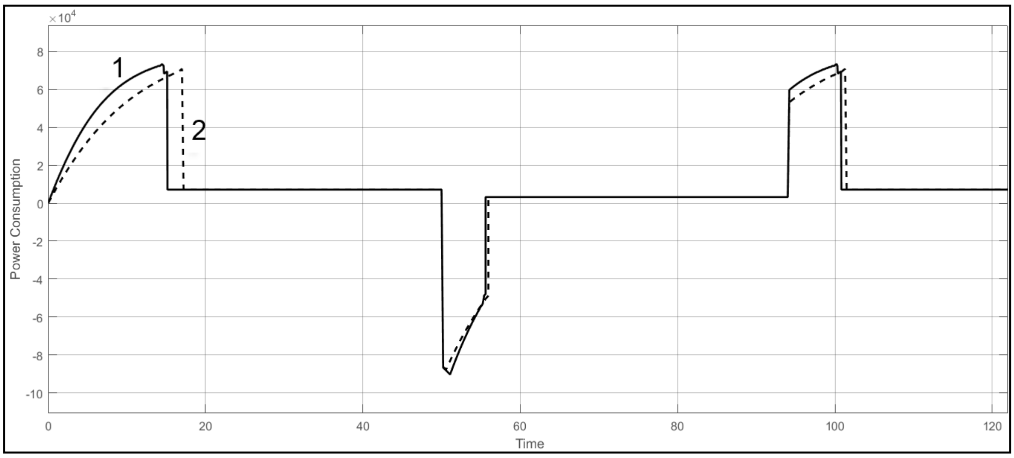

Figure 5.11. First and second Fuzzy systems effect on power consumption (W/s)

The second and third experiments were related with the changes in the input and output range of fuzzy membership function to examine controller response effect on vehicle acceleration/deceleration. Changing input and output range (Table 5.5) resulted in different fuzzification and defuzzification behavior of fuzzy model. For the second experiment, third model was designed with decreasing interval of input and output fuzzy rule range from [-150, +150] to [-75, +75] to improve the performance of controller. This performance change directly resulted in increment in power consumption in acceleration phase of vehicle (Figure 5.12). Energy regeneration was more than second model because deceleration performance of the vehicle was faster in the third model (Figure 5.13).

Table 5.5. Second and third Fuzzy models parameters

Fuzzy Models	**Second Model**	**Third Model**
Input Range	[-150,+150]	[-75,+75]
Input Membership Function Type	trimf	trimf
Output Range	[0,+150]	[0,+75]
Output Membership Function Type	trimf	trimf

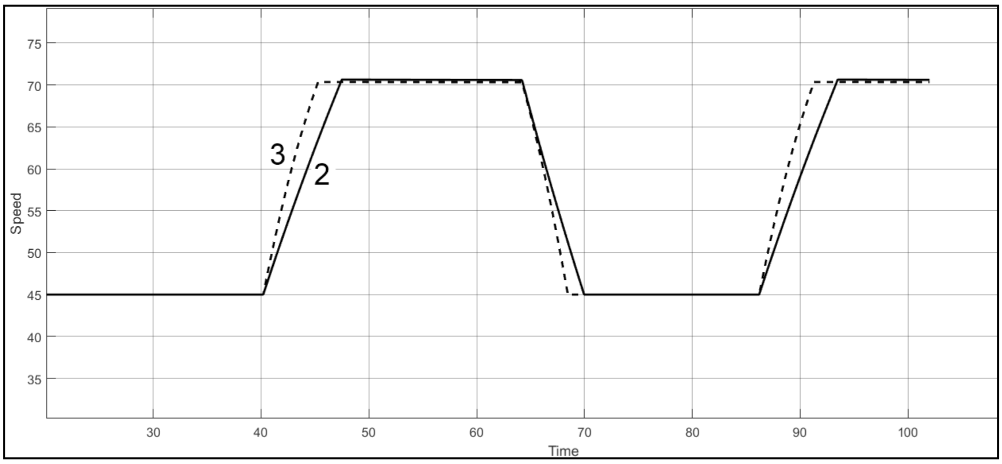

Figure 5.12. Second and third Fuzzy systems effect on vehicle speed (km-h/s)

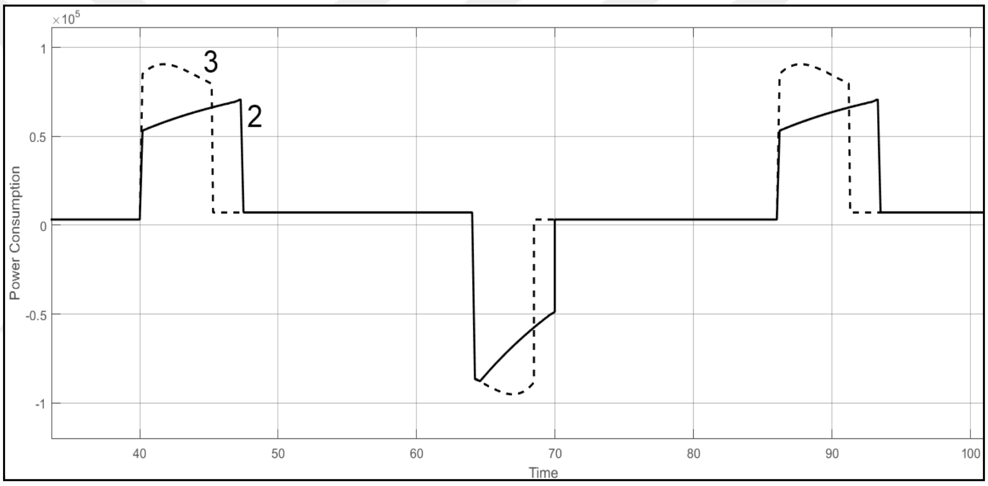

Figure 5.13. Second and third Fuzzy systems effect on power consumption (W/s)

The input and output range had been increased from [-75, +75] to [-350, +350] (Table 5.6) to observe slow response effect of designing fuzzy controller on vehicle power consumption. Fuzzification and defuzzification behavior was smoother than the first, second and third models. Additionally, the vehicle speed had slower response than all previous models in acceleration and deceleration performance (Figure 5.14). This performance changes directly resulted in more travelling range when power consumption had been considered in acceleration period (Figure 5.15). This behavior was expected because slower acceleration meant less power consumption. It was vice versa for deceleration phase.

Table 5.6. Third and fourth Fuzzy models parameters

Fuzzy Models	Third Model	Fourth Model
Input Range	[-75,+75]	[-350,+350]
Input Membership Function Type	trimf	trimf
Output Range	[0,+75]	[0,+350]
Ouput Membership Function Type	trimf	trimf

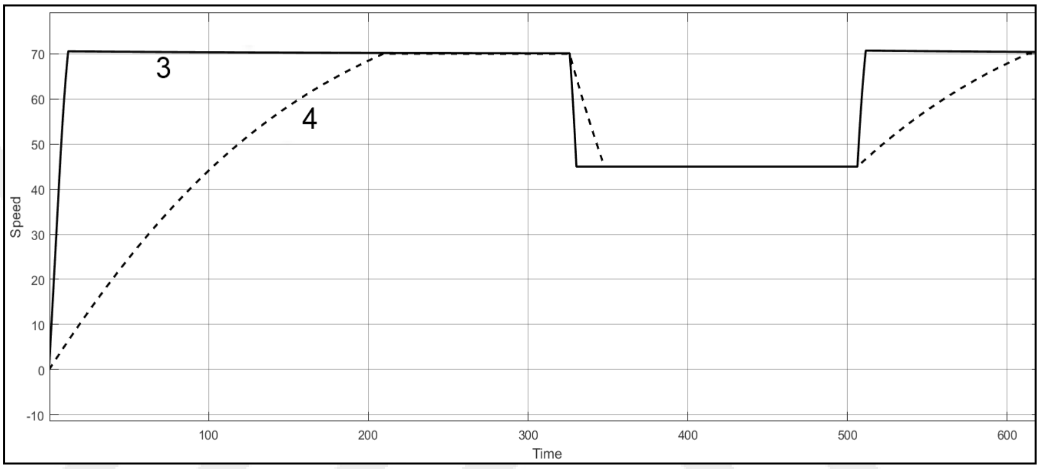

Figure 5.14. Third and fourth Fuzzy systems effect on vehicle speed (km-h/s)

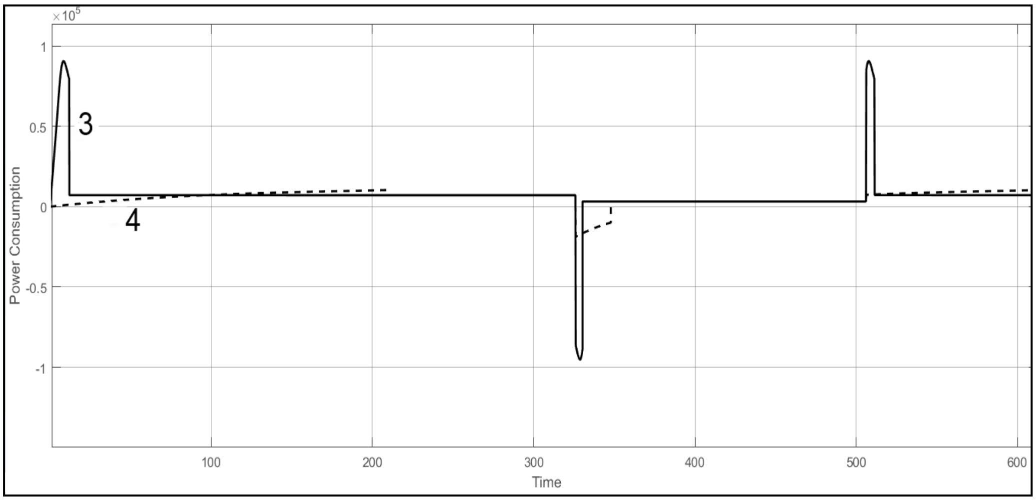

Figure 5.15. Third and fourth Fuzzy systems effect on power consumption (W/s)

5.3. MPC CONTROLLER PARAMETERS EFFECTS ON ACC SYSTEM BEHAVIOR AND EFFICIENCY

There are three key controller parameters when designing a system with MPC which are prediction horizon (T_p), control horizon (T_c) and sample time (δ). The controller predicts the dynamic behavior of the system over a prediction horizon (as a future prediction), and determines the input over a control horizon based on the measurements (reference (ref) value and measured plant output (mo)) obtained at time t. Control horizon is always smaller than Tp. This process is repeated for each sampling time with control and prediction horizon shifting forward [49,50].

Different MPC configuration was set to understand vehicle acceleration/deceleration performance, and power consumption effects of MPC controller parameters. Firstly, control horizon time was evaluated. Secondly, prediction horizon effect was analyzed with keeping sample and control horizon time constant. Lastly, three MPC systems were configured with different sample time to understand sample time effect on vehicle speed behavior, which would affect the performance.

MPC parameters for three different models of the first model to third model were given in Table 5.7. All models sample time and prediction horizon time were chosen as 1 and 10 seconds to see control horizon effect in wide range between 6-8 sec intervals. It was observed that decreasing of controlling horizon served acceleration, and deceleration performance of the vehicle was faster than the second and third model. This meant that if the controlling horizon was too low, the controller capability of the quick response was improved (Figure 5.16). Additionally, this performance changing directly resulted power consumption increasing in acceleration interval (Figure 5.17).

Table 5.7. All MPC models parameters for control horizon experiments

MPC Models	**First Model**	**Second Model**	**Third Model**
Sample Time(s)	1	1	1
Prediction Horizon(s)	10	10	10
Control Horizon(s)	6	7	8

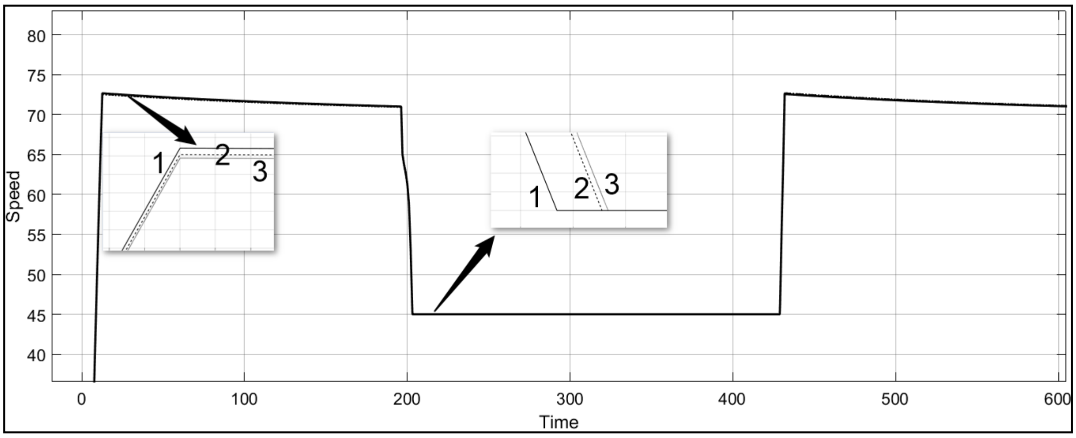

Figure 5.16. MPC control horizon effect on vehicle speed (km-h/s)

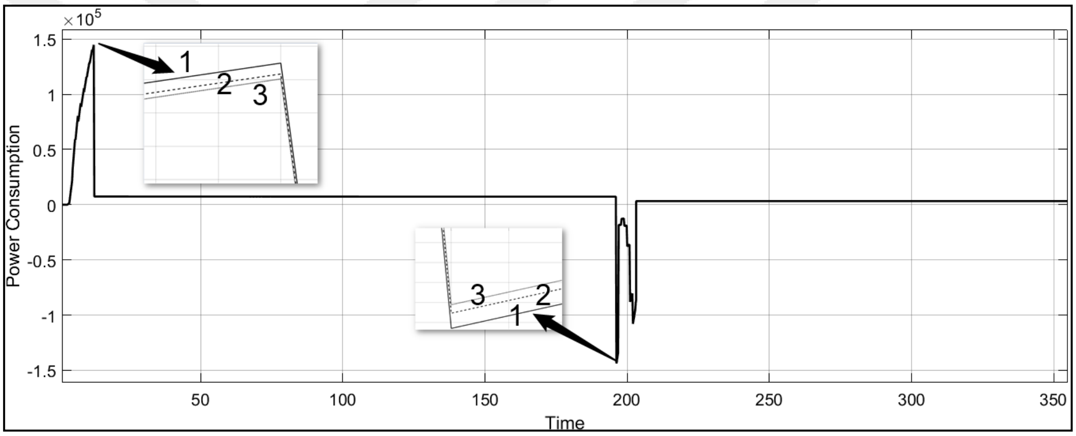

Figure 5.17. MPC control horizon effect on power consumption (W/s)

The second experiment was related to change in prediction horizon effect (T_p) on ACC system. Fourth, fifth and sixth models were created with 1 second sample time, and 2 second control horizon. Prediction horizon of the controllers was increased from 2 seconds to 100 seconds (Table 5.8). When plant output (vehicle speed) of each models were analyzed, then it could be seen that sixth model transient feedback was faster than fifth and fourth model (Figure 5.18). It was verified that prediction horizon increasing improved output reaction of the controller. When the power consumption effect was analyzed, then it could be seen that fourth model of the power consumption (acceleration) was higher than the other ones. The main reason of this behavior was the increase in vehicle acceleration (Figure 5.19). Regeneration of the EV battery in sixth model was much than the other models because sixth model deceleration performance was faster than the other ones.

Table 5.8. All MPC models parameters for prediction horizon experiments

MPC Models	Fourth Model	Fifth Model	Sixth Model
Sample Time(s)	1	1	1
Prediction Horizon(s)	2	10	100
Control Horizon(s)	2	2	2

Figure 5.18. MPC prediction horizon effect on vehicle speed (km-h/s)

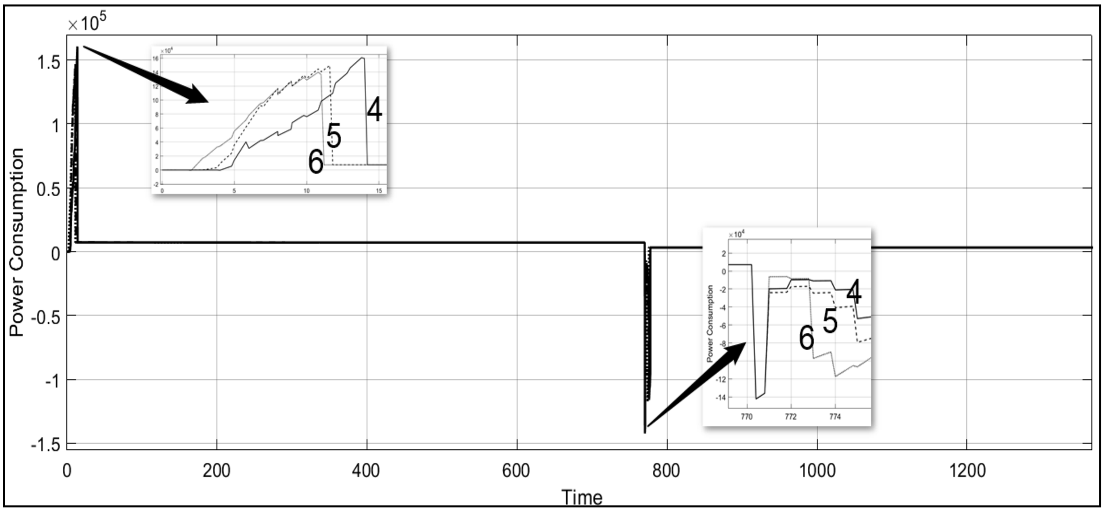

Figure 5.19. MPC prediction horizon effect on power consumption (W/s)

Three MPC models were created to understand the sample time parameter effect of MPC controller on vehicle speed and consumption parameters (Table 5.9). In these parameters, all prediction horizons were chosen as 10 seconds. 2 seconds was described for all MPC control horizon because control horizon of the MPC had to be less than prediction horizon (according to the MPC theory [49]). Sample time was chosen as 0.1, 1 and 5 seconds for seventh model, eighth and ninth model.

It was observed that when the sample time of MPC controller had increased, then the transient response of the controller was slower. For instance, seventh model sample time was less than the other ones. Thus, the vehicle reached 70 km/h (driver set speed) faster than the other MPC models (Figure 5.20). When the power consumption effect had been analyzed, it had been seen that ninth model of the power consumption (acceleration) was higher than the other ones because of the slope of vehicle acceleration (Figure 5.21). The performance changing resulted less travelling range for ninth model since the usage of instant torque of the engine was increased in acceleration period.

Table 5.9. All MPC models parameters for sample time experiments

MPC Models	**Seventh Model**	**Eighth Model**	**Ninth Model**
Sample Time(s)	0.1	1	5
Prediction Horizon(s)	10	10	10
Control Horizon(s)	2	2	2

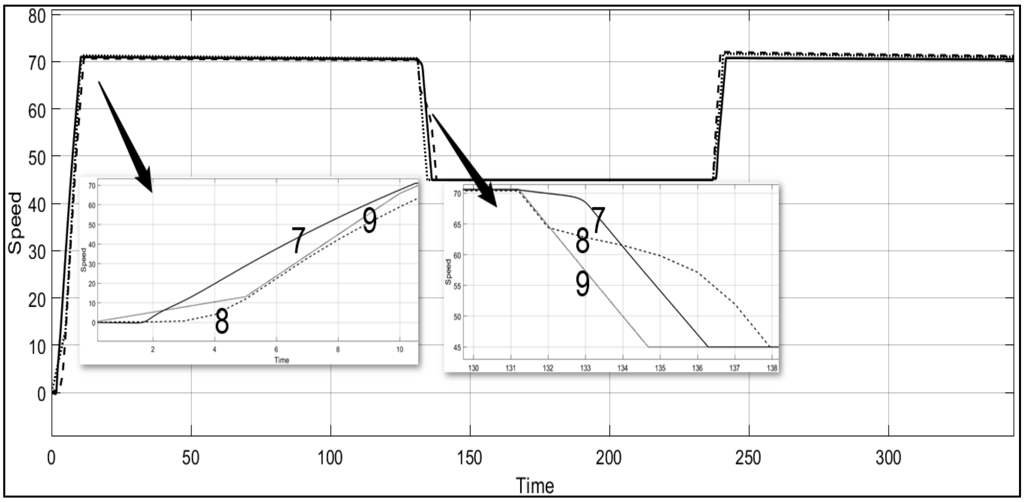

Figure 5.20. MPC sample time effect on vehicle speed (km-h/s)

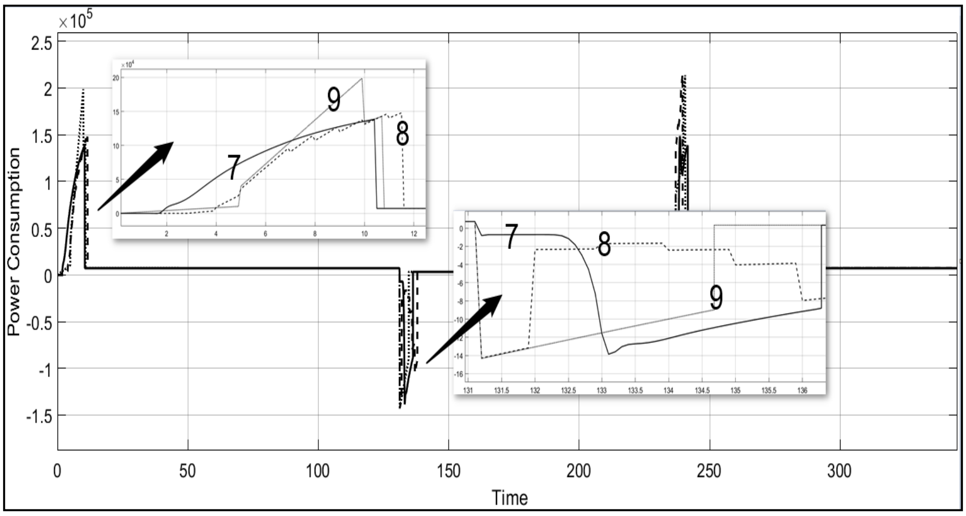

Figure 5.21. MPC prediction horizon effect on power consumption (W/s)

6. DISCUSSION AND CONCLUSION

Efficiency, carbon emission and performance are the important advantageous of the electric vehicles when it is compared with internal combustion engine. However, high battery costs, long charging time, low limited range, and limited charging infrastructures are problems that researchers are still working on. These problems are the reasons of the low number of electric vehicles in the roads. Changing physical and chemical battery characteristic and its management systems are some of the proposed studies to increase travelling range of electric vehicles. Furthermore, new vehicle technologies such as regenerative braking systems or ADAS systems have also been used on the electric vehicles to increase battery range. Adaptive Cruise Control (ACC), which is one of the Advanced Driving Assistance Systems (ADAS) systems, has also been used to increase the travelling range of electric vehicles without compromising the safety.

The aim of this thesis is to compare acceleration and deceleration performance by looking at the vehicle speed, torque map and power consumption characteristic of the electric vehicle when different controllers (PID, Fuzzy and MPC) are used for ACC. Different control parameters are selected to investigate the changes in the performance, and power consumption of the electric vehicle.

In this study, first the mathematical model of the longitudinal motion dynamic of electric vehicle has been extracted. In this model, tractive force, aerodynamic resistance, acceleration force, gravitational force, and rolling resistance equations have been put into Newton second law equation. All these forces are extracted and included into the dynamic equations. The model of the power consumption has been taken from the literature studies [32–36]. Then, PID, Fuzzy and MPC controllers have been integrated into this dynamic model of the electric vehicle. PID tuning tool in MATLAB/Simulink [45] have been used to decide the PID gains. Fuzzy logic designer tool in MATLAB/Simulink [51] have been used to change the fuzzy logic parameters. MPC configuration is directly set using MPC Designer APP in MATLAB/Simulink [43].

A scenario has been developed to evaluate the performance in acceleration/deceleration, and power consumption of designed ACC system with PID, Fuzzy and MPC controllers. This scenario demonstrates a typical ACC working use-case in real-life and used for three controller types (PID, Fuzzy and MPC). In this scenario, the driver sets the cruising speed assuming there is no vehicle in the front. The power consumption has been evaluated with considering the vehicle acceleration performance in this interval (0 to 70 km/h). When the vehicle reaches the desired speed, then there is a time interval that the vehicle is in constant speed. Later, the vehicle has a lower speed then the cruised value (that means the driver uses brakes – which is introduced by the sensing module). In this case, vehicle decelerates in a short period of time. The deceleration performance, and power consumption of the vehicle have also been analysed in this time interval.

PID parameters (Proportional, Integral, and Derivative) have been changed in methodological approach (increasing or decreasing step by step with a constant time interval). The response and transient behavior of the electric vehicle have been investigated when the parameters changed. It has been noticed that when PID parameters (Proportional =0.1654, Integral=0.0003, Derivative=-2.35 and Filter Coefficient= 0.080) are selected then the electric vehicle has a slower, and smooth response transient speed, which affect power consumption positively in acceleration period. However, because of the transient speed response has been slow in deceleration phase; low level regeneration of battery energy is effective in this interval. It has been also observed that the oscillation (which is important in the stability) of the electric vehicle speed cause extra power consumption for the vehicle not only in acceleration, and deceleration phase but also steady-state conditions when filter coefficient (N) is decreased. It is noticed that when there is a change in the parameter, then the steady state error and settling time performance of vehicle speed change which effects the power consumption of battery.

Fuzzy controller has also been investigated by changing input-output fuzzy membership function range, and membership function type to see acceleration/deceleration performance of each fuzzy configuration. In this study, *trimf* and *z shape* membership function type given in MATLAB/Simulink [44] have been used. When *z shape* membership function has been used, then it is observed that vehicle speed transient behavior has been more aggressive than *trimf* function, and settling time has been shorter which results in more power consumption for the vehicles in acceleration period. It has also been observed that changing input-output membership fuzzy range interval has more effect on instantaneous power consumption than membership function type because of the sensitivity tolerance of the fuzzy. It is noticed that decreasing interval of input and output fuzzy rule range from [-

150, +150] to [-75, +75] improve the acceleration performance of the vehicle. This performance change directly results in increment of power consumption in acceleration phase of vehicle, which is a negative effect on energy efficiency. On the other hand increasing of this interval results more energy regeneration in deceleration phase of the ACC. This fuzzy configuration can be used to obtain more energy from powertrain to the battery in the short period.

There are three key controller parameters when designing a system with MPC which are prediction horizon (T_p), control horizon (T_c) and sample time (δ). The effects of these parameters on the vehicle speed-torque performance, and power consumption have also been investigated. It has been observed that power consumption of the vehicle dramatically increases when the parameters have been selected towards the acceleration performance increase direction. Decreasing of control horizon (from 8 to 6 sec), prediction horizon (100 to 2 sec) and increasing sample time (0.1 to 5 sec) cause battery power consumption increase. When deceleration performance is considered then it is noticed that regeneration of the electric vehicle battery is much in short time period. Additionally, when T_p and T_c are increased, and δ is decreased then a change in the positive direction for power consumption is noticed in the acceleration interval.

In this thesis, ACC system is evaluated only in simulation environment using different controllers. As a future work, the experiments will be performed in real-time on the real electric vehicle. A radar or lidar module will be placed into the vehicle and engine control module. Other road and traffic conditions such as different weather conditions or up and down road conditions will be included into the model. Stop and go traffic effects on battery consumption will also be investigated.

Optimization of each controller parameter is another study that will be done in the future considering performance and power consumption of the electric vehicle. In this study, we compare electric vehicle performance and power consumption when different PID parameters (Proportional, Integral, and Derivative), Fuzzy controller parameters (input-output membership functions and types) and MPC parameters (prediction horizon, control horizon, and sample time) are used. However, there is no optimum solution introduced for each controller parameters to reach energy efficient ACC design. In the future, electric vehicle battery consumption could be defined in optimization problem to find the best parameter for each controller.

The developed controller behaviors will also be integrated with traffic data or GPS/Internet based navigation system to define electronic horizon in the future. The geometric description of the road that is curvature or slope can be reached from this electronic horizon. The speed profile (acceleration, deceleration) and controller parameters will be considered according the horizon without compromising safety criteria, which may improve energy efficiency of ACC technology in positive direction.

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